Ain Shams Engineering Journal (2016) xxx, xxx–xxx

Ain Shams University
Ain Shams Engineering Journal
www.elsevier.com/locate/asej
www.sciencedirect.com

ELECTRICAL ENGINEERING

Opposition-based krill herd algorithm applied to economic load dispatch problem

Sk Md Ali Bulbul [a,*], Moumita Pradhan [b], Provas Kumar Roy [c], Tandra Pal [d]

[a] *Department of Electrical Engineering, Bengal College of Engineering and Technology, Durgapur, West Bengal, India*
[b] *Department of Computer Science and Engineering, Dr. B C Roy Engineering College, Durgapur, West Bengal, India*
[c] *Department of Electrical Engineering, Jalpaiguri Government Engineering College, Jalpaiguri, West Bengal, India*
[d] *Department of Computer Science and Engineering, National Institute of Technology, Durgapur, West Bengal, India*

Received 31 August 2015; revised 21 January 2016; accepted 23 February 2016

KEYWORDS

Economic load dispatch;
Valve point loading;
Opposition based learning;
Krill herd algorithm

Abstract Economic load dispatch (ELD) is the process of allocating the committed units such that the constraints imposed are satisfied and the production cost is minimized. This paper presents a novel and heuristic algorithm for solving complex ELD problem, by employing a comparatively new method named krill herd algorithm (OKHA). KHA is nature-inspired metaheuristics which mimics the herding behaviour of ocean krill individuals. In this article, KHA is combined with opposition based learning (OBL) to improve the convergence speed and accuracy of the basic KHA algorithm. The proposed approach is found to provide optimal results while working with several operational constraints in ELD and valve point loading. The effectiveness of the proposed method is examined and validated by carrying out numerical tests on five different standard systems. Comparing the numerical results with other well established methods affirms the proficiency and robustness of proposed algorithm over other existing methods.

1. Introduction

Computational intelligence is an emerging trend in different research areas in power system due to its ability to synthesize largely interconnected and complex system very quickly and accurately. Economic load dispatch (ELD) is one of the most fundamental and important areas in power system operation and planning. The main objective of ELD problem was to schedule a set of real power delivered by online generation resources to fulfil the required demand at any time subject to a set of constraints [1,2] related to unit and system technical limits, at minimum production cost. The overall problem of ELD can be formalized as a non-smooth, highly nonlinear constrained optimization problem particularly for larger systems. The fuel cost component is related to variable cost of electricity generation, reflected in the electricity bills.

The existing methods to solve ELD problem can be divided into two major groups: classical methods and heuristic

* Corresponding author at: Bengal College of Engineering and Technology, Durgapur 713206, West Bengal, India. Fax: +91 3432503424.
E-mail address: sss.bulbul@gmail.com (S.M.A. Bulbul).
Peer review under responsibility of Ain Shams University.

ELSEVIER Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.asej.2016.02.003
2090-4479 © 2016 Faculty of Engineering, Ain Shams University. Production and hosting by Elsevier B.V.

Nomenclature

$F_i(P_{gi})$	fuel cost of the i-th generating unit
P_{gi}	real power generation of the i-th generating unit
a_i, b_i, c_i	quadratic cost coefficient of the i-th generator
N_g	total number of committed generators
e_i, f_i	cost coefficients of the i-th generator representing valve-point effect
P_L	power loss of the transmission network
B_{00}, B_{0i}, B_{ij}	transmission loss coefficients
$P_{gi}^{\max}, P_{gi}^{\min}$	upper and lower limits of power generation capacity of the i-th unit
P_{gi}^0	previous operating point of the i-th unit
DR_i, UR_i	down rate and up rate limits, respectively, of the i-th unit
np_i i	number of prohibited zones of the i-th unit
$P_{gi,j}^l, P_{gi,j-1}^u$	lower and upper generation limits of prohibited zone j and $j-1$ of the i-th unit
$S_{\min}$	Minimum spinning reserve of the system
S_i i	Spinning reserve of the i-th unit
$v_i^{\max}$	maximum induced speed
v_i^k, v_i^{k-1}	induced motion of the i-th krill at the k-th and $(k-1)$-th movement
ω_n	inertia weight of the induced motion
$\alpha_i^{new}, \alpha_i^{target}$	local and the target effect of the i-th krill
f_w, f_b	worst and the best position among all krill individuals of the population
f_i, f_j	fitness value of the i-th and j-th krill individuals
S	number of krill individuals surrounding the particular krill
i	current iteration number
$i_{\max}$	maximum iteration number
N_P	population is size
z_i, z_j	position of the i-th and the j-th krill
ω_x	inertia weight of the foraging motion
$v_{f_i}^{k-1}, v_{f_i}^k$	foraging motion of the i-th krill at k-th and $(k-1)$-th movement
$v_d^{\max}$	maximum diffusion motion
λ	directional vector uniformly distributed between $(-1, 1)$
N	total number of control variables
U_i, L_i	upper and lower limits of the i-th control variable
c_t	position constant

methods. Some of the classical optimization techniques such as gradient method [3], linear programming (LP) [4], nonlinear programming (NLP) [5], quadratic programming (QP) [6], base point (BP) method [7] and interior point (IP) method [8] have been applied for solving ELD problem. Very recently, Yang et al. [9] presented an analytical method named quadratically constrained programming (QCP). In classical approach ELD problem is assumed to be a smooth and monotonically increasing continuous quadratic function. Despite the fact that some of these techniques have excellent convergence characteristics, various methods among them suffer from convergence as the global or local solution is highly sensitive to the initial guess. These methods have also severe difficulty in handling discrete variables. The validation of this supposition sacrifices considerable precision. Dynamic programming algorithm (DP) [10] does not approximate the cost curves but may suffer from "curse of dimensionality" and "local optimality".

However single quadratic function or piecewise quadratic function to represent the input–output characteristics (or cost function) in ELD does not solve the purpose in practical system. Higher-order nonlinearities and discontinuities are observed in real input–output characteristics. So various researchers propose higher order cost function for less approximation, better curve fitting of running cost to get more practical, accurate and reliable results. A nonlinear characteristic of the cost curve arises because of ramp rate limits [11], discontinuous prohibited operating zones [12] and multi-fuel effects [13]. Ramp rate limits arise because of generation resources in the actual operating processes is restricted that unit generation output cannot be changed instantaneously. Prohibited zones are the consequence of physical limitations of individual power plant components such as boilers, feed pumps. The amplification of vibrations in a shaft bearing at certain operating regions may lead to instabilities in operation for certain loads. The presence of prohibited zones for individual generator leads to a solution space with disjoint, non-convex, infeasible regions. Multi-fuel options based on availability of sources such as coal, nature gas, or oil, lead to determine most economic fuel to burn. Due to the aforesaid facts an alternative to the classical approaches, population-based (a class of meta-heuristics) optimization techniques are introduced in recent times. Some of these techniques introduced by earlier scholars are as follows: artificial immune system (AIS) [14], ant colony optimization (ACO) [15], gravitational search algorithm (GSA) [16], tabu search (TS) [17], simulated annealing (SA) [18], bacterial foraging (BF) [19], differential evolution (DE) [20], teaching–learning based optimization (TLBO) [21–23], firefly algorithm (FA) [24], genetic algorithm (GA) [25], particle swarm optimization (PSO) [26,27], biogeography based optimization (BBO) [28], and artificial bee colony (ABC) [29]. AIS is based on function of biological immune system. In fact, AIS copies the method which the human body acquires immunity using vaccination against diseases. In AIS, the decision points and solutions are antibodies and antigens in the immune system which are employed to solve optimization problems. ACO utilizes the foraging behaviour of real ants. When searching for food, these ants initially explore the area by performing a randomized walk from the nest to the food source and ants deposit pheromone on the ground in order to mark some favourable path to guide other ants to the food source. GSA is based on the physical law of gravity and the law of motion. In GSA a set of agents called masses have been proposed to find the optimum solution by simulation. TS is basically local search algorithm inspired by the human memory. It explicitly relies on history of the search, both to escape from local minima and to implement an explorative strategy. SA is a stochastic optimization approach inspired by the natural process of annealing related to thermodynamics. The main advantage of SA approach is that it does not need large computer memory and also it has ability to

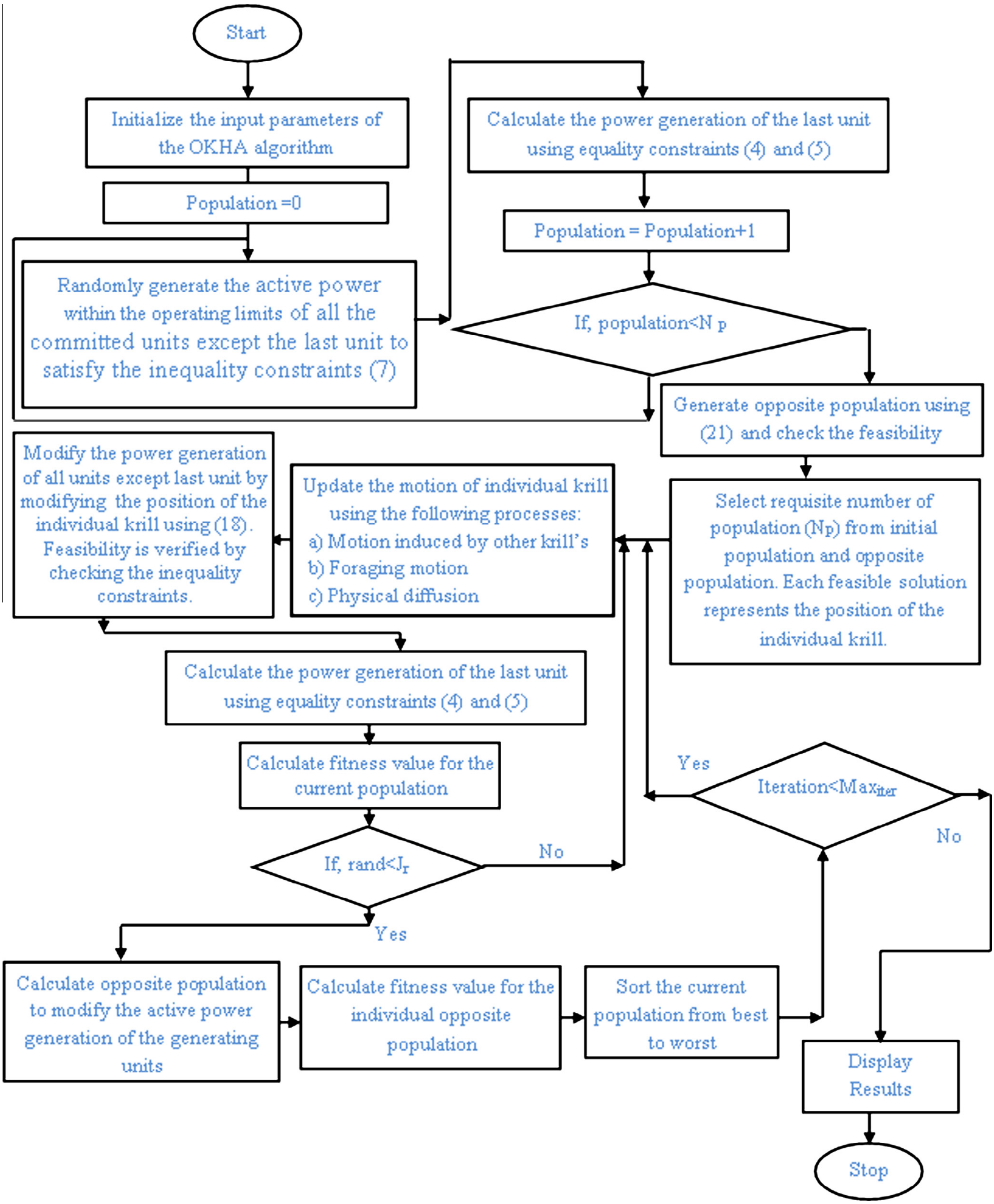

Figure 1 Flowchart of OKHA algorithm applied to ELD.

escape from local minima by incorporating a probability function in accepting and rejecting new solutions. SA algorithm also needs appropriate selection of control parameter before implementation to get fitness convergence. BF utilizes social foraging behaviour of Escherichia coli bacteria present in the human intestines. TLBO is a teaching–learning process

Table 1 Fuel cost with different population size for 10-unit system.

Population size	Fuel cost ($/h)	Computational time (sec)	Population size	Fuel cost ($/h)	Computational time (sec)
40	612.3423	3.03	100	605.6449	3.96
50	611.0172	3.27	110	605.6449	4.08
60	610.2360	3.59	120	605.6449	4.17
70	609.1325	3.75	130	605.6449	4.31
80	608.0054	3.88	140	605.6449	4.46
90	606.8621	3.93	150	605.6449	4.57

inspired algorithm based on the effect of influence of a teacher on the output of learners in a class. TLBO consists of two phases called as teacher phase and student phase. In the teacher phase, the student having minimum objective function value is assigned as a teacher. The other students in the current population are modified as neighbourhood of the teacher. In student phase, all modified students are compared with each other to increase their knowledge. FA is a nature-inspired algorithm which is based on the flashing behaviour of fireflies. GA has recently found extensive applications in solving global optimization searching problems when the closed-form optimization technique cannot be applied. Genetic algorithms (GAs) are parallel and global search techniques that emulate natural genetic operators. The algorithm of PSO emulates from behaviour of animals societies that don't have any leader in their group or swarm, such as bird flocking and fish schooling. Position and velocity of the particles are updated in a heuristic manner using guidance from particles' own experience and the experience of its neighbours. BBO is an innovative approach based on the biography describing natural ways of distributing species over a vast geographical area, i.e., how species migrate, arise and become extinct. ABC uses the dynamics of the insects because of different actions and interactions of individuals with each other as well as with their environment according to the location of a food source and the quality of the solution is represented by the nectar amount of the source (fitness). Sahoo et al. in his recent endeavour presented cuckoo search algorithm (CSA) [30] to solve five different non-convex ELD problems.

These heuristic techniques have the ability to provide fast and efficient solution, but sometimes they suffer from discovering global optimal solution, slow convergence rate and several parameters tuning.

To accommodate with complex problem some hybrid algorithms are introduced such as quantum-inspired PSO (QPSO) [31], modified group search optimizer algorithm (MGSO) [32], oppositional BBO (OBBO) [33], quasi-oppositional BBO (QOBBO) [34], hybrid DE algorithm based on PSO (DE/PSO) [35], Gbest guided ABC (GABC) [36], hybrid PSO and GSA (HPSO–GSA) [37] have been applied to solve the ELD problem. HPSO–GSA was successfully applied to some of the test systems such as standard IEEE 30-bus, 6, 10 and 40-unit system and confirms the effectiveness over some well-established algorithms. Shuffled differential evolution (SDE) [38] developed by Reddy and Vaisakh was effectively applied on standard 3-unit, 13-unit and 40-unit system. Incremental ABC with local search (IABC-LS) [39] was tested on 6-bus 3-unit, 14-bus 5-unit, and 30-bus 6-unit and 40-generator systems and confirms its quality of potential to solve such kind of problem. A novel uniform distributed two-stage particle swarm optimization (UDTPSO) algorithm [40] was successfully implemented by Suresh et al. to solve unified power flow controller (UPFC) based ELD problem. Recently, Kumar et al. proposed modified BAT algorithm [41] to solve optimal power flow problem in the presence of IPFC including system constraints and device limits. Roy et al. proposed hybrid chemical reaction optimization approach [42] to solve ELD problem considering various nonlinearities such as valve point loading effect, multiple fuel, prohibited operating zone and ramp rate constraints. Chen et al. developed a penalty function-hybrid direct search method (PF-HDSM) [43] for the solution of multi-area wind-thermal coordination dispatch (MWCD) problem. Ghasemi suggested pareto based multi-objective interactive honey bee mating optimization (MHBMO) [44] for solving the CEED problem. Reddy et al. expressed a hybrid shuffled differential evolution (SDE) [38] algorithm which combined the benefits of shuffled frog leaping algorithm and DE. Roy et al. proposed chemical reaction optimization (CRO) algorithm [45] for solving dynamic economic emission dispatch (DEED) problem of power systems.

Krill herd algorithm (KHA) [46] is a recently developed algorithm based on swarm intelligence of Krill species. It is based on herding behaviour of krill creatures found mostly in Antarctic. The herding of the krill individuals is a multi-objective process including two steps: (1) increasing krill density and (2) reaching food. The position of an individual krill is time dependent and it is governed by the following factors: movement induced by other krill individuals, foraging activity and random diffusion. The main advantages of proposed algorithm are (i) higher degree of convergence than the other population based optimization techniques such as GA, FA, BFOA, PSO, GSA, (ii) takes less iteration cycles to reach global minima, and (iii) has higher efficiency in terms of CPU time. Having knowledge of all these discussions, this paper addressed design and implementation of OKHA to solve LFC problem. By utilizing opposition based learning, fitter starting candidate solutions can be obtained even when there is no a priori knowledge about the solution(s). By staying within variables' interval static boundaries, we would jump outside the already shrunken search space by applying opposite points. Through these steps of opposition based learning, the overall performance of KHA algorithm is enhanced by finding global optimal solutions.

The proposed OKHA technique is applied on five standard test cases namely 6-unit system with ramp rate and prohibited operating zone, 10-thermal generating units considering valve point effect and multi-fuel options, 40-unit with transmission loss with valve point loading, a large scale system consisting of 140 thermal generating units and a wind-fossil fuel based 6-unit power system. For each case a comparative study of

Table 2 Comparative analysis in terms of generation and fuel cost of different algorithms for 6-unit system.

Unit	OKHA	IPSO-TVAC [12]	BFO [19]	MTS [49]	PSO [54]	GA [54]	NPSO_LRS [54]	NAPSO [56]	SOH-PSO [57]	HHS [58]	IPSO [55]
1	447.3988	447.5840	449.4600	448.1277	447.5823	462.0444	446.9600	446.4232	438.2100	447.4960	440.5711
2	173.2409	173.2010	172.8800	172.8082	172.8387	189.4456	173.3944	172.6080	172.5800	173.3140	179.8365
3	263.3815	263.3310	263.4100	262.5932	261.3300	254.8535	262.3436	262.6183	257.4200	263.4450	261.3798
4	138.9802	138.8520	143.4900	136.9605	138.6812	127.4296	139.5120	142.7752	141.0900	139.0550	131.9134
5	165.3914	165.3280	164.9100	168.2031	169.6781	151.5388	164.7089	164.6650	179.3700	165.4750	170.9823
6	87.0520	87.1500	81.2520	87.3304	74.8963	90.7150	89.0162	86.3230	86.8800	87.1250	90.8241
TL	12.4448	12.4460	12.4020	13.0205	13.0066	13.0260	12.9351	12.4127	12.5500	12.9500	12.5480
Cost ($/h)		15,443.063	15,443.84	15,450.060	15,450.140	15,457.960	15,450.00	15,443.7656	15,446.0200	15,449.000	15,444.000

Table 3 Statistical comparison for 50 trials among various methods for 6-unit system.

Techniques →	OKHA	IPSO-TVAC [12]	BFO [19]	MTS [49]	PSO [54]	NPSO-LRS [54]	GA [54]	NAPSO [56]	SOH-PSO [57]	HHS [58]	IPSO [55]
Best cost ($/h)	15,443.075	15,443.063	15,443.8497	15,450.06	15,450.14	15,450.00	15,457.96	15,443.7656	15,446.02	15,449.00	15,444.00
Worst cost ($/h)	15,443.916	15,445.114	NA	15,453.64	15,492.0	15,452.00	15,524.00	15,443.7657	15,609.64	15,453.00	NA
Mean cost ($/h)	15,443.327	15,443.582	15,446.9538	15,451.17	15,454.00	15,450.50	15,469.00	15,443.7657	15,497.35	15,450.00	15,446.30

simulation results is given to establish the efficiency and robustness of the algorithm.

The rest of this paper is organized as follows: mathematical problem formulation is represented in Section 2. The proposed KHA is briefly described in Section 3. Opposition based learning concept is briefly explained in Section 4. Section 5 presents different steps.

OKHA algorithm is applied to ELD problem. Section 6, illustrates the test system and numerical performance of the proposed algorithm compared with other recently developed algorithms such as PSO-LRS, NPSO, NPSO-LRS, APSO, CBPSO-RVM, KHA, GA-API, SDE, TLBO, and QOTLBO. Finally, the paper is concluded in Section 7.

2. Mathematical problem formulation

2.1. Objective function

The basic operation of ELD involves the best utilization of the available generating units subjected to various soft and hard constraints to transfer electrical energy to the consumers without sacrificing the quality at minimum cost. To determine the economic distribution of load among the online units of a plant, the variable operating costs of each unit must be expressed in terms of its power output. The input–output relation of a thermal unit, which is known as ''heat-rate curve'' is converted to the fuel cost curve representing the relationship of the operating cost of a fossil-fired thermal unit with its output power.

The objective function of ELD without considering valve point loading is usually represented as a quadratic cost function of real power as follows:

$$\text{Minimize} \quad F_t = \left(\sum_{i=1}^{Ng} F_i(P_{gi})\right) = \left(\sum_{i=1}^{Ng} a_i + b_i P_{gi} + c_i P_{gi}^2\right) \tag{1}$$

where $F_i(P_{gi})$ is the fuel cost of generating i-th unit, P_{gi} is the real power generation of unit i. a_i, b_i and c_i are the heat rate data of the i-th generator and N_g is the total number of commited generators.

Due to the valve-point loading effect the objective function discontinuous, non-convex with multiple minima. The objective function is then represented as follows:

$$F_t = \left(\sum_{i=1}^{Ng} F_i(P_{gi})\right) = \left(\sum_{i=1}^{Ng} a_i + b_i P_{gi} + c_i P_{gi}^2 + \left| e_i \times \sin\left(f_i \times \left(P_{gi}^{\min} - P_{gi}\right)\right)\right|\right) \tag{2}$$

where e_i, f_i are the coefficients of i-th generator with valve-point loading effect.

For a more realistic representation, some generating units are supplied with multiple fuel sources. So the problem of determining the most economical fuel to burn is a big concern. To get a more accurate model of ELD problem can be represented by several quadratic functions.

$$F_i(P_{gi}) = \begin{cases} a_{i1} + b_{i1} P_{gi} + c_{i1} P_{gi}^2 + \left| e_{i1} \times \sin\left(f_{i1} \times \left(P_{gi}^{\min} - P_{g1}\right)\right)\right| & \textit{fuel type} \quad 1 \\ a_{i2} + b_{i2} P_{gi} + c_{i2} P_{gi}^2 + \left| e_{i2} \times \sin\left(f_{i2} \times \left(P_{gi}^{\min} - P_{gi}\right)\right)\right| & \textit{fuel type} \quad 2 \\ \vdots & \\ a_{ik} + b_{ik} P_{gi} + c_{ik} P_{gi}^2 + \left| e_{ik} \times \sin\left(f_{ik} \times \left(P_{gi}^{\min} - P_{gi}\right)\right)\right| & \textit{fuel type} \quad k \end{cases} \tag{3}$$

2.2. Constraints

The following constraints must be satisfied when carried out optimization on ELD.

2.2.1. System real power balance constraint

When transmission loss is not considered, total real power generation by committed generators is equal to only the power demand in that period.

$$\sum_{i=1}^{Ng} P_{gi} = P_D \tag{4}$$

By considering transmission losses the total generated power of all on-line generators must satisfy the total demand plus the transmission loss.

$$\sum_{i=i}^{Ng} P_{gi} = P_D + P_L \tag{5}$$

where P_L is the transmission loss which depends on generated power P_i. Numerically, P_L the transmission loss formula known as Kron's loss formula or the B-coefficient formula, is given by

$$P_L = \sum_{i=1}^{Ng}\sum_{j=1}^{Ng} P_{gi} B_{ij} P_{gj} + \sum_{i=1}^{Ng} B_{0i} P_{gi} + B_{00} \tag{6}$$

where B_{00}, B_{0i} and B_{ij} are the loss coefficients, which is assumed to be constant under a normal operating condition.

2.2.2. Generator capacity constraints

The maximum active power of each unit is limited by the thermal consideration and also minimum power generation is limited by flame instability of a boiler. This can be expressed as

$$P_{gi}^{\min} \leqslant P_{gi} \leqslant P_{gi}^{\max} \tag{7}$$

where $P_{gi}^{\max}$ is the upper limit of power generation capacity of i-th unit. On the other hand, if the power output is less than a pre-specified value $P_{gi}^{\min}$, the unit is not put on the bus bar because it is not possible to generate that low value of power from the unit.

2.2.3. Ramp rate constraints

The operating range of the practical generating units is restricted by their ramp up/down rate limits which may mathematically be expressed as follows:

$$\text{Max}\left(P_{gi}^{\min}, P_{gi}^0 - DR_i\right) \leqslant P_{gi} \leqslant \text{Min}\left(P_{gi}^{\max}, P_{gi}^0 + UR_i\right) \tag{8}$$

where P_{gi}^0 is the previous operating point of the i-th unit, DR_i, UR_i are the down rate and up rate limits, respectively, of the i-th unit.

Please cite this article in press as: Bulbul SMA et al., Opposition-based krill herd algorithm applied to economic load dispatch problem, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.02.003

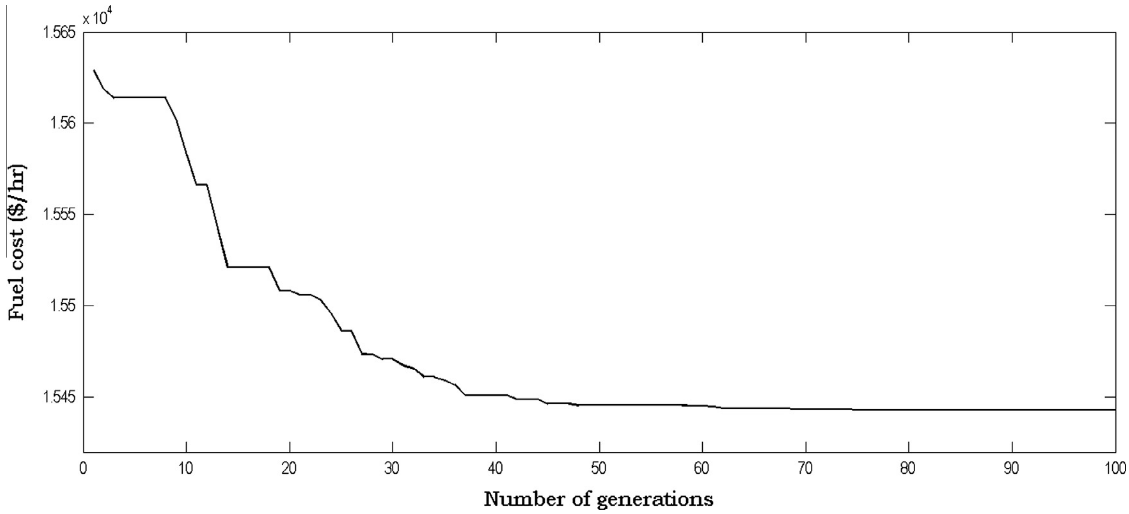

Figure 2 Cost convergence characteristic of OKHA algorithm for 6-unit system with ramp rate and prohibited operating zone.

Table 4 Best solution for test system-2 with a demand of 2700 MW.

Unit no	PSO-LRS [59]		NPSO [59]		NPSO-LRS [59]		APSO (2) [54]		CBPSO-RVM [50]		KHA-IV [47]		OKHA	
	Fuel type	Gen (MW)	Fuel type	Gen (MW)	Fuel type	Gen (MW)	Fuel type	Gen (MW)	Fuel type	Gen (MW)	Fuel type	Gen (MW)	Fuel type	Gen (MW)
1	2	219.0155	2	220.6570	2	223.3352	2	223.3377	2	219.2073	2	212.3865	2	214.4684
2	1	213.8901	1	211.7859	1	212.1957	1	212.1547	1	210.2203	3	208.7381	3	208.9873
3	1	283.7616	1	280.4062	1	276.2167	1	276.2203	1	278.5456	2	332.5949	2	332.0575
4	3	237.2687	3	238.6013	3	239.4187	3	239.4176	3	239.3704	3	236.4131	3	238.1622
5	1	286.0163	1	277.5621	1	274.6470	1	274.6411	1	276.412	1	270.0975	1	269.2157
6	3	239.3987	3	239.1204	3	239.7974	3	239.7953	3	240.5797	3	237.6310	3	238.5653
7	1	291.1767	1	292.1397	1	285.5388	1	285.5406	1	292.3267	1	280.7793	1	280.612
8	3	241.4398	3	239.1530	3	240.6323	3	240.627	3	237.7557	3	239.1042	3	237.6241
9	3	416.9721	3	426.1142	3	429.2637	3	429.3104	3	429.4008	3	414.9190	3	413.8705
10	1	271.0623	1	274.4637	1	278.9541	1	278.9553	1	276.1815	1	267.3368	1	266.4366
TC ($/h)	624.2297		624.1624		624.1273		624.0145		623.9588		605.7582		605.6449	

Table 5 Comparison of statistical results of various methods for test system-2 (10-unit without loss and with multi-fuel effects).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)
PSO-LRS [59]	624.2297	625.7887	628.3214
NPSO [59]	624.1624	625.2180	627.4237
NPSO-LRS [59]	624.1237	624.9985	626.9981
APSO (2) [54]	624.0145	624.8185	627.3049
CBPSO-RVM [50]	623.9588	624.0816	624.2930
KHA-IV [47]	605.7582	605.8043	605.9426
OKHA	605.6449	605.6984	605.8236

2.2.4. Prohibited operating zone constraints

In the presence of physical operation limitation such as faults in the machines, boiler, and feed pumps, generating units may have prohibited operating regions. For the i-th unit with POZs, the feasible operating zones can be described as follows:

$$\begin{aligned} &P_{gi}^{\min} \leqslant P_{gi} \leqslant P_{gi,1}^{l} \\ &P_{gi,j-1}^{u} \leqslant P_{gi} \leqslant P_{gi,j}^{l}, \quad j = 2,3,\ldots,np_i \\ &P_{gi,np_i}^{u} \leqslant P_{gi} \leqslant P_{gi}^{\max} \end{aligned} \tag{9}$$

where np_i is the number of prohibited zones of i-th unit, $P_{gi,j}^{l}$, $P_{gi,j-1}^{u}$ are the lower and upper generation limits of prohibited zones j and $j-1$, respectively, of the i-th unit.

2.2.5. Spinning reserve

The total spinning reserve of all the units together must be greater than or equal to the minimum spinning reserve of the system and is given by the following:

$$\sum_{i=1}^{NG} S_i \geqslant S_{\min} \tag{10}$$

Please cite this article in press as: Bulbul SMA et al., Opposition-based krill herd algorithm applied to economic load dispatch problem, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.02.003

Table 6 Best solution for test system-3 with a demand of 10,500 MW (40-unit with loss and valve point loading effects).

Unit no	GA-API [52]	SDE [38]	TLBO [21]	QOTLBO [21]	KHA-IV [47]	OKHA
1	114	110.06	114	114.0000	114.0000	114.0000
2	114	112.41	114	114.0000	114.0000	114.0000
3	120	120.00	120	107.8221	120.0000	120.0000
4	190	188.72	182.4448	190.0000	190.0000	182.5880
5	97	85.91	90.6923	88.3702	88.5944	88.3011
6	140	140.00	140	140.0000	105.5166	140.0000
7	300	250.19	300	300.0000	300.0000	300.0000
8	300	290.68	296.0682	300.0000	300.0000	300.0000
9	300	300.00	288.8518	300.0000	300.0000	300.0000
10	205.25	282.01	281.9520	211.2071	280.6777	279.5994
11	226.30	180.82	238.1293	317.2766	243.5399	243.6246
12	204.72	168.74	251.0120	163.7603	168.8017	168.7592
13	346.48	469.96	483.1175	481.5709	484.1198	484.0490
14	434.32	484.17	481.9042	480.5462	484.1662	484.0362
15	431.34	487.73	488.2883	483.7683	485.2375	484.0367
16	440.22	482.30	396.3448	480.2998	485.0698	484.0704
17	500	499.64	494.2577	489.2488	489.4539	489.2827
18	500	411.32	408.3826	489.5524	489.3035	489.4094
19	550	510.47	510.5206	512.5482	510.7127	511.3137
20	550	542.04	521.2217	514.2914	511.3040	511.3323
21	550	544.81	540.5700	527.0877	524.4678	523.3375
22	550	550.00	522.1852	530.1025	535.5799	526.8873
23	550	550.00	526.1804	524.2912	523.3795	523.3242
24	550	528.16	521.1967	524.6512	523.15527	523.2762
25	550	524.16	525.8010	525.0586	524.1916	523.2985
26	550	539.10	526.0022	524.4654	523.5453	523.4107
27	11.44	10.00	13.0804	10.8929	10.1245	10.0129
28	11.56	10.37	11.0397	17.4312	10.1815	10.0020
29	11.42	10.00	12.9373	12.7839	10.0229	10.0215
30	97	96.10	89.7412	88.8119	87.8154	87.8017
31	190	185.85	190.0000	190.0000	190.0000	190.0000
32	190	189.54	190.0000	190.0000	190.0000	190.0000
33	190	189.96	190.0000	190.0000	190.0000	190.0000
34	200	199.90	200.0000	200.0000	200.0000	200.0000
35	200	196.25	200.0000	168.0873	164.9199	164.8057
36	200	185.85	164.7435	165.5072	164.9787	164.8113
37	110	109.72	110.0000	110.0000	110.0000	110.0000
38	110	110.00	110.0000	110.0000	110.0000	110.0000
39	110	95.71	110.0000	110.0000	110.0000	110.0000
40	550	532.47	547.9677	511.5313	512.06775	511.2844
TC ($/h)	139,864.96	138,157.46	137,814.17	137,329.86	136,670.37	136,575.968
TL (MW)	1045.06	974.43	1002.63	1008.96	978.9251	990.68

where $S_{\min}$ is the minimum spinning reserve of the system, S_i is the spinning reserve of the i-th unit i which is given by the following:

$$S_i = \min\left(P_{G_i}^{\max} - P_{G_i}, S_i^{\max}\right) \tag{11}$$

3. Krill herd algorithm

In 2012, Krill herd algorithm (KHA) [46] was introduced by Gandomi and Alavi for global optimization. It is relatively new, efficient generic stochastic optimization technique mimics the herding behaviour of krill individuals. The objective function for the krill movement is defined by the minimum distances of each individual krill from food source and from higher density of the herd. The individual Krill position in multidimensional space is time-dependent and decided by the following actions:

(i) movement affected by other krill individuals,
(ii) foraging action and,
(iii) random physical diffusion.

These operators are briefly explained as follows:

3.1. Movement affected by other krill individuals

In this phase, krill movement in the multi-dimensional problem space is affected by other krill individuals. The motion induced is dynamically adjusted by the target swarm density, local swarm density and a repulsive swarm density. Mathematically the velocity of i-th krill is defined by [46,47]:

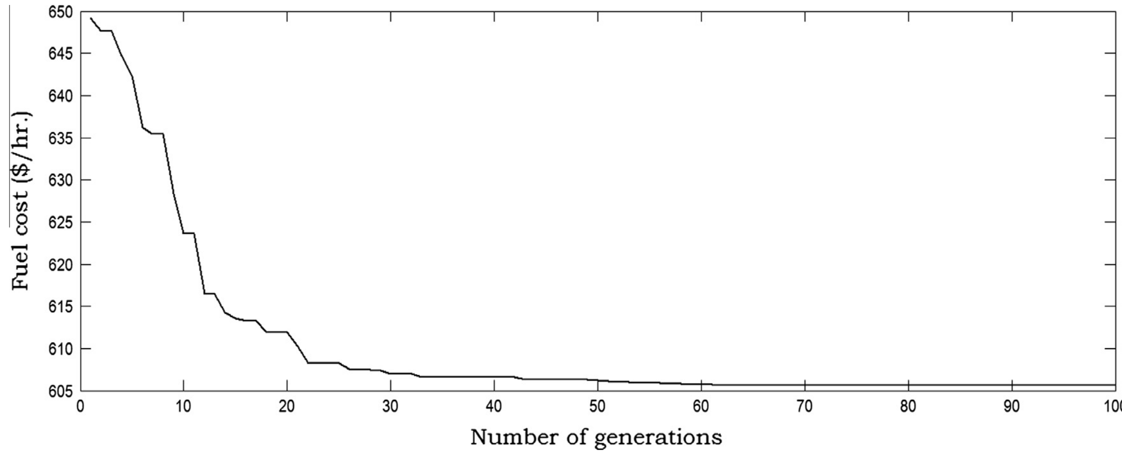

Figure 3 Cost convergence characteristic of OKHA algorithm for 10-unit system with multi-fuel and valve point loading.

Table 7 Comparison of statistical results of various methods for test system-3 (40-unit with loss and valve-point loading effects).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)
GA-API [52]	139,864.96	NA	NA
SDE [38]	138,157.46	NA	NA
TLBO [21]	137,814.17	NA	NA
QOTLBO [21]	137,329.86	NA	NA
KHA-IV [47]	136,670.37	136,671.24	136,671.86
OKHA	136,575.97	136,576.15	136,576.64

$$v_i^k = a_i v_i^{\max} + \omega_n v_i^{k-1} \tag{12}$$

where

$$\alpha_i = \alpha_i^{new} + \alpha_i^{target} \tag{13}$$

$$\alpha_i^{new} = \sum_{j=1}^{S} f_{i,j} z_{i,j} \tag{14}$$

$$z_{i,j} = \frac{z_i - z_j}{|z_i - z_j| + rand(0,1)} \tag{15}$$

$$f_{i,j} = \frac{f_i - f_j}{f_w - f_b} \tag{16}$$

$$\alpha_i^{target} = 2\left(rand(0,1) + \frac{i}{i_{\max}}\right) f_i^{best} x_i^{best} \tag{17}$$

where $v_i^{\max}$ is the maximum induced speed; v_i^k, v_i^{k-1} are the induced motion of the i-th krill at the k-th and $(k-1)$-th movement; ω_n is the inertia weight of the motion induced in the range $[0,1]$; $\alpha_i^{new}, \alpha_i^{target}$ are the local and the target effect, respectively; f_w and f_b are the worst and the best position respectively, among all krill individuals, of the population; f_i,f_j are the fitness value of i-th and j-th individuals respectively; S is the number of krill individuals surrounding the particular krill; i is the current iteration number and $i_{\max}$ is the maximum iteration number.

To identify the neighbouring members of each krill individual, a sensing distance (S_{d_i}) parameter is used. If the distance between the two individual krill is less than the sensing distance, that particular krill is considered as neighbour of the other krill. The sensing distance may be defined by [46,47]:

$$sd_i = \frac{1}{5N_P} \sum_{j=1}^{N_P} |z_i - z_j| \tag{18}$$

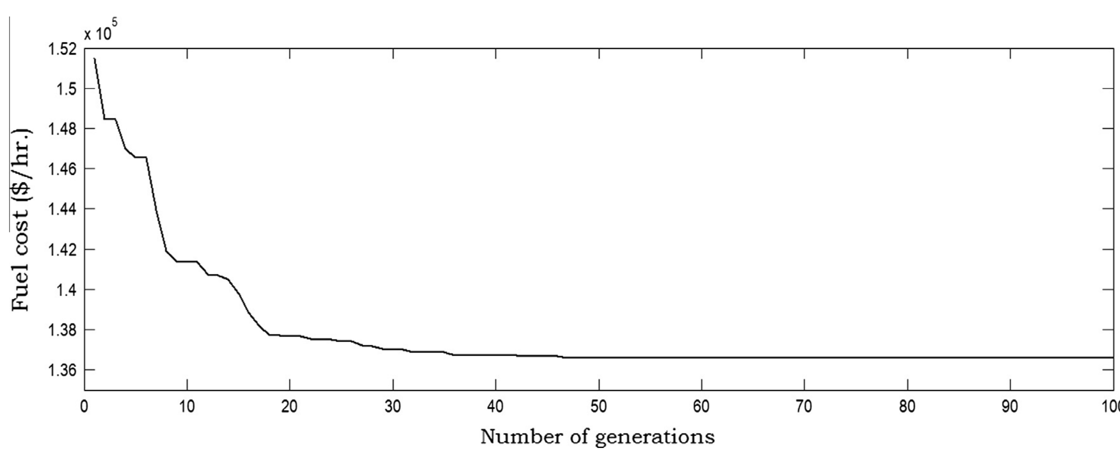

Figure 4 Cost convergence characteristic of OKHA algorithm for 40-unit system with loss.

Table 8 Best solution for test system-4 with a demand of 49,342 MW (140-unit without loss).

Unit no	GEN (MW)			Unit no	GEN (MW)			Unit no	GEN (MW)		
	SDE [38]	KHA	OKHA		SDE [38]	KHA	OKHA		SDE [38]	KHA	OKHA
1	116.1654	118.3326	119	48	250	249	250	95	978	978	978
2	189	188.9995	189	49	250	250	250	96	682	682	682
3	190	189.9912	189.0012	50	250	250	250	97	720	719.6	720
4	190	189.2245	188.4245	51	165	165	165	98	718	717.8	718
5	168.5398	169.0012	169.1249	52	165	165	165	99	720	720	720
6	190	189.9832	189.9998	53	165	166	165	100	964	964	964
7	490	489.9968	490	54	165	165	165	101	*958*	958	958
8	490	489.9996	490	55	180	180	180	102	1007	1006.6667	1007
9	496	495.9902	496	56	180	180	180	103	1006	1005.998	1006
10	496	496	496	57	103	103.9942	103	104	1013	1013	1013
11	496	495.9993	496	58	198	199.0001	198	105	1020	1020	1020
12	496	496	496	59	312	311.99	312	106	954	954	954
13	506	505.965	506	60	281.8008	280.9912	281.9129	107	952	951	952
14	509	509	509	61	163	163	163	108	1006	1006	1006
15	506	505.9234	506	62	95	95	95	109	1013	1013	1013
16	505	504.9946	505	63	160.0001	160	160.2321	110	1021	1020.8998	1021
17	506	506	506	64	160	160	160	111	1015	1014.9989	1015
18	506	506	506	65	490	490	490	112	94	94.0001	94
19	505	504.9966	505	66	196.0001	201.2341	201.2341	113	94	94.1	94
20	505	504.9093	505	67	490	490	490	114	94	94	94
21	505	505	505	68	489.9999	488.1256	488.1256	115	244	244	244
22	505	504.9992	505	69	130	130	130	116	244	244.9	244
23	505	504.8982	505	70	234.7198	234.9838	233.9938	117	244	244	244
24	505	504.9668	505	71	137	137	137	118	95	95.6	95
25	537	536.9000	537	72	325.4956	325.9969	326.9969	119	95	95.0011	95
26	537	537	537	73	195	195	195	120	116	116.001	116
27	549	549	549	74	175	175	175	121	175	175.0032	175
28	549	549	549	75	175	175	175	122	2	2	2
29	501	501	501	76	175.0001	180	176	123	4	4	4
30	501	501	501	77	175	175	175	124	15	15.0002	15
31	506	506	506	78	330	330	330	125	9	9.2001	9
32	506	506	506	79	531	531	531	126	12	12.1001	12
33	506	506	506	80	531	531	531	127	10	10	10
34	506	506	506	81	368.6177	366.6179	367.6176	128	112	112.0042	112
35	500	500	500	82	56	56.2212	56	129	4	4.4262	4
36	500	500	500	83	115	115.2236	115	130	5	5.0022	5
37	241	241	241	84	115	115	115	131	5	5.0012	5
38	241	241	241	85	115	115	115	132	50	51.998	50
39	774	774	774	86	207	207	207	133	5	5.9942	5.5666
40	769	769	769	87	207	207	207	134	42	42.9922	43.3363
41	3	3	3	88	175	175	175	135	42	42.9942	43.1223
42	3	3	3	89	175	175	175	136	41	41	41
43	249.9989	250	250	90	175	175	175	137	17	17	17
44	247.1855	249.9922	249.9911	91	175	175	175	138	18.9992	7.6659	12.7652
45	250	250	250	92	580	580	580	139	7	7.0042	8.112
46	250	250	250	93	645	645	645	140	39.1813	26.0486	27.1470
47	242.2959	248.7789	248.2960	94	984	984	984	TC($/h)	1,560,236.85	1,560,173.88	1,560,146.95

where N_P the population is size; z_i and z_j are the position of the i-th and j-th krill, respectively.

3.2. Foraging action

Each individual krill adjusts its foraging velocity based on two factors: its own current food location and previous experience about the food location which is mathematically defined as follows [46,47]:

$$v_{f_i}^k = 0.02\partial_i + \omega_x v_{f_i}^{k-1} \tag{19}$$

$$\partial_i = 2\left(1 - \frac{i}{i_{\max}}\right) f_i \frac{\sum_{j=1}^{S} \frac{z_j}{f_j}}{\sum_{j=1}^{N_S} \frac{1}{f_j}} + f_i^{best} x_i^{best} \tag{20}$$

where ω_x the inertia weight of the foraging is motion; $v_{f_i}^{k-1}$, $v_{f_i}^{k}$ is the foraging motion of the i-th krill at k-th and $(k-1)$-th movement.

3.3. Random diffusion

The diffusion process of the krill individuals is considered as a random phenomenon. It may be represented in terms of a

Table 9 Comparison of statistical results of various methods for test system-4 (140-unit without loss).

Methods	Best cost ($/h)	Mean cost ($/h)	Worst cost ($/h)
SDE [38]	1,560,236.85	NA	NA
KHA	1,560,173.88	1,560,176.7448	1,560,177.8061
OKHA	1,560,146.95	1,560,148.9264	1,560,149.9764

maximum diffusion speed and a random directional factor and may mathematically be expressed by [46,47]:

$$v_{d_i}^k = \lambda v_d^{\max} \tag{21}$$

where $v_d^{\max}$ the maximum diffusion is motion; λ is the directional vector uniformly distributed between $(-1, 1)$.

3.4. Position update

Finally, the position of the i-th krill during the time interval t to Δt may be expressed as [46,47]:

$$z_i(t + \Delta t) = z_i(t) + \Delta t\left(v_i^k + v_{f_i}^k + v_{d_i}^k\right) \tag{22}$$

where

$$\Delta t = c_t \sum_{i=1}^{N} (U_i - L_i) \tag{23}$$

where N is the total number of control variables; U_i, L_i are the upper and lower limits of the i-th control variable; c_t is the position constant factor.

4. Oppositional based learning

Opposition-based learning (OBL) [48] is an effective concept to enhance various optimization approaches. The main idea behind OBL is the simultaneous consideration of corresponding opposite estimate as a second set of candidate solutions to achieve a better approximation for the current candidate solution. It has been proved an opposite candidate solution increases the chance to be closer to the global optimum solution than a randomly chosen candidate solution.

Opposite of a number x can be calculated using the following equation:

$$\overline{x} = a + b - x \tag{24}$$

where $\forall x \in R$ in the interval $[a, b]$. Similarly the aforesaid definition can be extended to multi-dimensions as follows:

$$\overline{x_j} = a_j + b_j - x_j \tag{25}$$

where $\forall x_j \in R$ in the interval $[a_j, b_j]$ and $j = 1, 2, \ldots, d$.

Let $P = (x_1, x_2, \ldots, x_d)$ be the point in d-dimensional space (i.e., a candidate solution). By definition of opposite points is $\overline{P} = (\overline{x_1}, \overline{x_2}, \ldots, \overline{x_d})$ .Now, if $f(\overline{P}) \geqslant f(P)$, then point P will be replaced with $\overline{P}$; otherwise, we continue with P. Therefore to continue with fitter solution the point and its opposite points should be evaluated simultaneously.

5. Implementation of OKHA for ELD problem

Generator active power output is the control variable in ELD problem. The computational procedure is briefly illustrated in the following section:

Step 1: Specify input parameters of the system like generator cost coefficients (a_i, b_i and c_i) and valve-point coefficients (e_i and f_i), total number of committed units N_g, capacity constraints of all generating units ($P_i^{\max}$ and $P_i^{\min}$), total load demand P_D. B -coefficients matrix in case of transmission loss. Initialize the OKHA parameters like the maximum induced speed, $v_i^{\max} = 0.01$; the maximum diffusion speed, $v_d^{\max} = 0.05$; the position constant factor, $c_t = 0.02$; the inertia weight constant factors, w_n, w_x as 0.9 to stimulate the global search capability of the algorithm and to exploit the exploration space the values are decreased linearly to 0.1.
Step 2: Initialize the active power generation of committed generating units randomly within the upper and lower capacity limits except the last unit. The last unit generation is evaluated by using equality constraints specified in (4) and (5) and this must be checked by the inequality constraints (7). If all equality and inequality constraints are satisfied, a feasible population set (P) is generated. Any violation of these constraints leads to non-feasible solution;

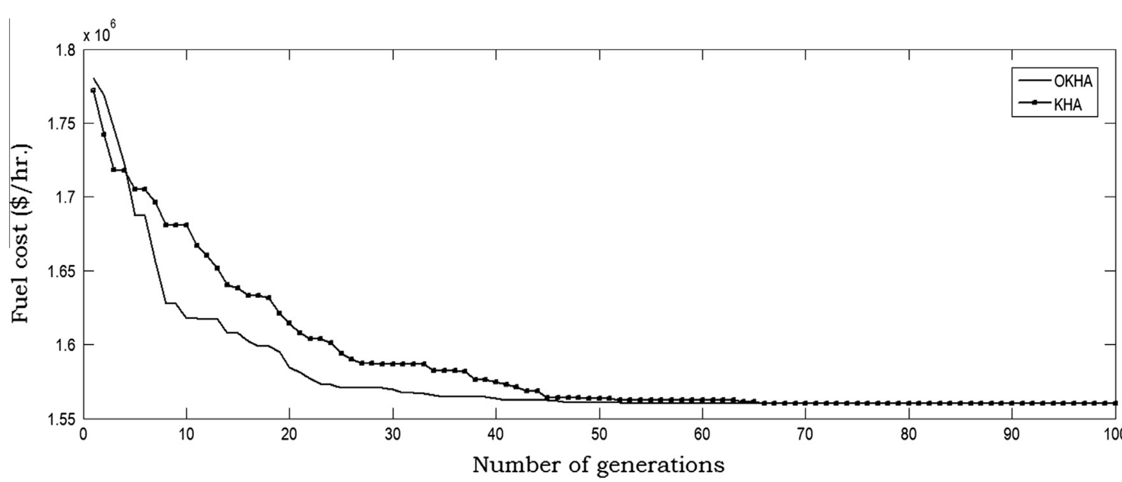

Figure 5 Cost convergence characteristics of KHA and OKHA algorithms for 140-unit system without loss.

Please cite this article in press as: Bulbul SMA et al., Opposition-based krill herd algorithm applied to economic load dispatch problem, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.02.003

Table 10 Comparison of results of various methods for test system-5 (**Wind-fossil fuel based 6-unit system**).

Units	Total generation cost minimization			
	QPSO [60]	GABC [61]	KHA	OKHA
P_{T1} (MW)	103.56	97.05	99.4904	99.5609
P_{T2} (MW)	99.09	100.00	99.4562	98.9916
P_{T3} (MW)	567.66	592.77	591.1364	591.5160
P_{G4} (MW)	211.64	110.08	110.0106	110.0123
P_{G5} (MW)	138.05	110.00	110.1328	110.0026
P_{O6} (MW)	40.25	40.12	40.0000	40.0000
P_{W7} (MW)	8.32	90.00	89.9624	89.9819
P_{W8} (MW)	31.42	59.97	59.8112	59.9347
FC ($/h)	NA	26,250.00	26,208.9566	26,201.3694
WC ($/h)	NA	1459.00	1457.9927	1458.6543
TC ($/h)	29,513.40	27,710.00	27,666.9493	27,660.0238

in that case population (P) should be reinitialized until it satisfies the constraints.

The ith krill individual is represented by n-th decision variables represented as

$$X = [X_{i,1} \quad X_{i,2} \quad X_{i,3} \quad \cdots \quad X_{i,n}] \tag{26}$$

If the population size is N, the matrix is created as follows:

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & \cdots & X_{1,n} \\ X_{2,1} & X_{2,2} & \cdots & \cdots & X_{2,n} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ X_{N,1} & X_{N,2} & \cdots & \cdots & X_{N,n} \end{bmatrix} \tag{27}$$

In ELD problem individual generator's real power output is the unknown variable so the corresponding matrix will be the following:

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & \cdots & P_{1,n} \\ P_{2,1} & P_{2,2} & \cdots & \cdots & P_{2,n} \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \cdots & \vdots \\ P_{N,1} & P_{N,2} & \cdots & \cdots & P_{N,n} \end{bmatrix} \tag{28}$$

where n is the total number of generators and N is number of agent sets (population size). Each element in the matrix P represents a potential solution to ELD problem.

Step 3: Create oppositional based population (OBP) using (25).

Step 4: Calculate the fitness function by using P and OBP corresponding to each agent using (1)–(3). Select fittest vectors from P and OBP according to the fitness function.

Step 5: Evaluate the krill individual motion by (12), (19), and (21) which describes the induction motion, foraging action and random diffusion of each krill respectively.

Step 6: Update the position of each krill individual using (22).

Step 7: Check the feasibility of all generation output by applying inequality constraint (7) except slack generator whether each unit violates the condition or not. If any of the generators violates the operating limit, it must be recomputed. The output of slack unit will be evaluated by using (4) and (5). If any infeasible solutions arise, it should replace by the best feasible solutions.

Step 8: Based on a jumping rate jr (i.e. jumping probability), OBP is generated and fitness value of the OBP is calculated.

Step 9: Select required number of fittest individuals from $\{P \cup \text{OBP}\}$ as current population.

Step 10: Go to Step 3 for next iteration until stopping criterion is not fulfilled. The stopping criterion in this case is the maximum number of cycles (iteration or generation).

The flowchart of the proposed OKHA algorithm applied to ELD is illustrated in Fig. 1.

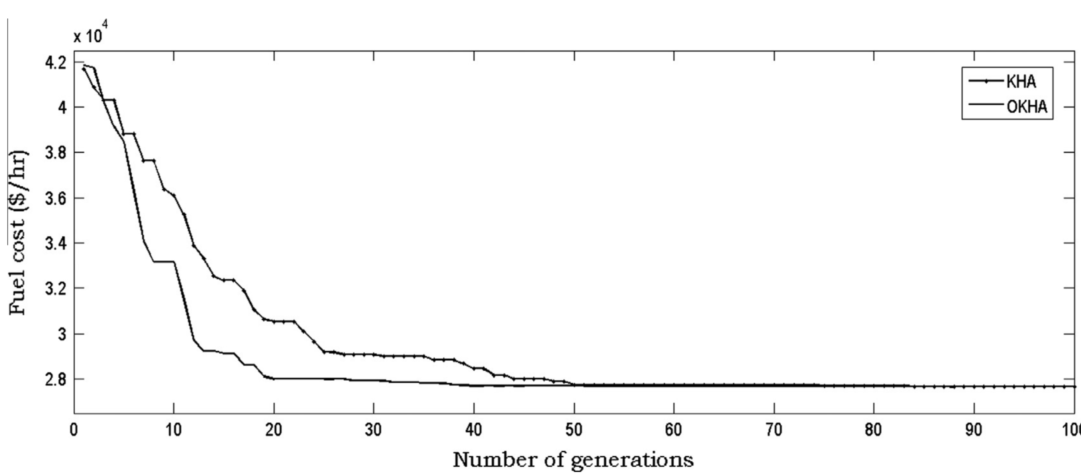

Figure 6 Cost convergence of KHA and OKHA algorithms for wind-fossil fuel based 6-unit system.

Table A1 System data of 140-unit system.

Unit	Pg^{min} (MW)	Pg^{max} (MW)	a (\$/MW^2 h)	b (\$/MW h)	c (\$/h)	d (\$/h)	e (rad/MW)	ur (MW)	dr (MW)	Po (MW)
Thermal 1	71	119	0.032888	61.242	1220.645	0	0	30	120	98.4
Thermal 2	120	189	0.00828	41.095	1315.118	0	0	30	120	134
Thermal 3	125	190	0.003849	46.31	874.288	0	0	60	60	141.5
Thermal 4	125	190	0.003849	46.31	874.288	0	0	60	60	183.3
Thermal 5	90	190	0.042468	54.242	1976.469	700	0.08	150	150	125
Thermal 6	90	190	0.014992	61.215	1338.087	0	0	150	150	91.3
Thermal 7	280	490	0.007039	11.791	1818.299	0	0	180	300	401.1
Thermal 8	280	490	0.003079	15.055	1133.978	0	0	180	300	329.5
Thermal 9	260	496	0.005063	13.226	1320.636	0	0	300	510	386.1
Thermal 10	260	496	0.005063	13.226	1320.636	600	0.055	300	510	427.3
Thermal 11	260	496	0.005063	13.226	1320.636	0	0	300	510	412.2
Thermal 12	260	496	0.003552	14.498	1106.539	0	0	300	510	370.1
Thermal 13	260	506	0.003901	14.651	1176.504	0	0	600	600	301.8
Thermal 14	260	509	0.003901	14.651	1176.504	0	0	600	600	368
Thermal 15	260	506	0.003901	14.651	1176.504	800	0.06	600	600	301.9
Thermal 16	260	505	0.003901	14.651	1176.504	0	0	600	600	476.4
Thermal 17	260	506	0.002393	15.669	1017.406	0	0	600	600	283.1
Thermal 18	260	506	0.002393	15.669	1017.406	0	0	600	600	414.1
Thermal 19	260	505	0.003684	14.656	1229.131	0	0	600	600	328
Thermal 20	260	505	0.003684	14.656	1229.131	0	0	600	600	389.4
Thermal 21	260	505	0.003684	14.656	1229.131	0	0	600	600	354.7
Thermal 22	260	505	0.003684	14.656	1229.131	600	0.05	600	600	262
Thermal 23	260	505	0.004004	14.378	1267.894	0	0	600	600	461.5
Thermal 24	260	505	0.003684	14.646	1229.131	0	0	600	600	371.6
Thermal 25	280	537	0.001619	16.261	975.926	0	0	300	300	462.6
Thermal 26	280	537	0.005093	13.362	1532.093	0	0	300	300	379.2
Thermal 27	280	549	0.000993	17.203	641.989	0	0	360	360	530.8
Thermal 28	280	549	0.000993	17.203	641.989	0	0	360	360	391.9
Thermal 29	260	501	0.002473	15.274	911.533	0	0	180	180	480.1
Thermal 30	260	501	0.002547	15.212	910.533	0	0	180	180	319
Thermal 31	260	506	0.003542	15.033	1074.81	0	0	600	600	329.5
Thermal 32	260	506	0.003542	15.033	1074.81	0	0	600	600	333.8
Thermal 33	260	506	0.003542	15.033	1074.81	600	0.043	600	600	390
Thermal 34	260	506	0.003542	15.033	1074.81	0	0	600	600	432
Thermal 35	260	500	0.003132	13.992	1278.46	0	0	660	660	402
Thermal 36	260	500	0.001323	15.679	861.742	0	0	900	900	428
Thermal 37	120	241	0.00295	16.542	408.834	0	0	180	180	178.4
Thermal 38	120	241	0.00295	16.542	408.834	0	0	180	180	194.1
Thermal 39	423	774	0.000991	16.518	1288.815	0	0	600	600	474
Thermal 40	423	769	0.001581	15.815	1436.251	600	0.043	600	600	609.8
Gas 1	3	19	0.90236	75.464	669.988	0	0	210	210	17.8
Gas 2	3	28	0.110295	129.544	134.544	0	0	366	366	6.9
Gas 3	160	250	0.024493	56.613	3427.912	0	0	702	702	224.3
Gas 4	160	250	0.029156	54.451	3751.772	0	0	702	702	210
Gas 5	160	250	0.024667	54.736	3918.78	0	0	702	702	212
Gas 6	160	250	0.016517	58.034	3379.58	0	0	702	702	200.8
Gas 7	160	250	0.026584	55.981	3345.296	0	0	702	702	220
Gas 8	160	250	0.00754	61.52	3138.754	0	0	702	702	232.9
Gas 9	160	250	0.01643	58.635	3453.05	0	0	702	702	168
Gas 10	160	250	0.045934	44.647	5119.3	0	0	702	702	208.4
Gas 11	165	504	0.000044	71.584	1898.415	0	0	1350	1350	443.9
Gas 12	165	504	0.000044	71.584	1898.415	1100	0.043	1350	1350	426
Gas 13	165	504	0.000044	71.584	1898.415	0	0	1350	1350	434.1
Gas 14	165	504	0.000044	71.584	1898.415	0	0	1350	1350	402.5
Gas 15	180	471	0.002528	85.12	2473.39	0	0	1350	1350	357.4
Gas 16	180	561	0.000131	87.682	2781.705	0	0	720	720	423
Gas 17	103	341	0.010372	69.532	5515.508	0	0	720	720	220
Gas 18	198	617	0.007627	78.339	3478.3	0	0	2700	2700	369.4
Gas 19	100	312	0.012464	58.172	6240.909	0	0	1500	1500	273.5
Gas 20	153	471	0.039441	46.636	9960.11	0	0	1656	1656	336
Gas 21	163	500	0.007278	76.947	3671.997	0	0	2160	2160	432
Gas 22	95	302	0.000044	80.761	1837.383	0	0	900	900	220
Gas 23	160	511	0.000044	70.136	3108.395	0	0	1200	1200	410.6

(*continued on next page*)

Table A1 (*continued*)

Unit	Pg^{min} (MW)	Pg^{max} (MW)	*a* ($/MW^2 h)	*b* ($/MW h)	*c* ($/h)	*d* ($/h)	*e* (rad/MW)	*ur* (MW)	*dr* (MW)	*Po* (MW)
Gas 24	160	511	0.000044	70.136	3108.395	0	0	1200	1200	422.7
Gas 25	196	490	0.018827	49.58	7095.484	0	0	1014	1014	351
Gas 26	196	490	0.010852	65.404	3392.732	0	0	1014	1014	296
Gas 27	196	490	0.018827	49.84	7095.484	0	0	1014	1014	411.1
Gas 28	196	490	0.018827	49.84	7095.484	0	0	1014	1014	263.2
Gas 29	130	432	0.03456	66.465	4288.32	0	0	1350	1350	370.3
Gas 30	130	432	0.08154	22.941	13,813	1200	0.03	1350	1350	418.7
Gas 31	137	455	0.023534	64.314	4435.493	0	0	1350	1350	409.6
Gas 32	137	455	0.035475	45.017	9750.75	1000	0.05	1350	1350	412
Gas 33	195	541	0.000915	70.644	1042.366	0	0	780	780	423.2
Gas 34	175	536	0.000044	70.959	1159.895	0	0	1650	1650	428
Gas 35	175	540	0.000044	70.959	1159.895	0	0	1650	1650	436
Gas 36	175	538	0.001307	70.302	1303.99	0	0	1650	1650	428
Gas 37	175	540	0.000392	70.662	1156.193	0	0	1650	1650	425
Gas 38	330	574	0.000087	71.101	2118.968	0	0	1620	1620	497.2
Gas 39	160	531	0.000521	37.854	779.519	0	0	1482	1482	510
Gas 40	160	531	0.000498	37.768	829.888	0	0	1482	1482	470
Gas 41	200	542	0.001046	67.983	2333.69	0	0	1668	1668	464.1
Gas 42	56	132	0.13205	77.838	2028.954	0	0	120	120	118.1
Gas 43	115	245	0.096968	63.671	4412.017	0	0	180	180	141.3
Gas 44	115	245	0.054868	79.548	2982.219	1000	0.05	120	180	132
Gas 45	115	245	0.054868	79.548	2982.219	0	0	120	180	135
Gas 46	207	307	0.014382	93.966	3174.939	0	0	120	180	252
Gas 47	207	307	0.013161	94.723	3218.359	0	0	120	180	221
Gas 48	175	345	0.016033	66.919	3723.822	0	0	318	318	245.9
Gas 49	175	345	0.013653	68.185	3551.405	0	0	318	318	247.9
Gas 50	175	345	0.028148	60.821	4322.615	0	0	318	318	183.6
Gas 51	175	345	0.01347	68.551	3493.739	0	0	318	318	288
Nuclear 1	360	580	0.000064	2.842	226.799	0	0	18	18	557.4
Nuclear 2	415	645	0.000252	2.946	382.932	0	0	18	18	529.5
Nuclear 3	795	984	0.000022	3.096	156.987	0	0	36	36	800.8
Nuclear 4	795	978	0.000022	3.04	154.484	0	0	36	36	801.5
Nuclear 5	578	682	0.000203	1.709	332.834	0	0	138	204	582.7
Nuclear 6	615	720	0.000198	1.668	326.599	0	0	144	216	680.7
Nuclear 7	612	718	0.000215	1.789	345.306	0	0	144	216	670.7
Nuclear 8	612	720	0.000218	1.815	350.372	0	0	144	216	651.7
Nuclear 9	758	964	0.000193	2.726	370.377	0	0	48	48	921
Nuclear 10	755	958	0.000197	2.732	367.067	0	0	48	48	916.8
Nuclear 11	750	1007	0.000324	2.651	124.875	0	0	36	54	911.9
Nuclear 12	750	1006	0.000344	2.798	130.785	0	0	36	54	898
Nuclear 13	713	1013	0.00069	1.595	878.746	0	0	30	30	905
Nuclear 14	718	1020	0.00065	1.503	827.959	0	0	30	30	846.5
Nuclear 15	791	954	0.000233	2.425	432.007	0	0	30	30	850.9
Nuclear 16	786	952	0.000239	2.499	445.606	0	0	30	30	843.7
Nuclear 17	795	1006	0.000261	2.674	467.223	0	0	36	36	841.4
Nuclear 18	795	1013	0.000259	2.692	475.94	0	0	36	36	835.7
Nuclear 19	795	1021	0.000707	1.633	899.462	0	0	36	36	828.8
Nuclear 20	795	1015	0.000786	1.816	1000.367	0	0	36	36	846
Oil1	94	203	0.014355	89.83	1269.132	0	0	120	120	179
Oil 2	94	203	0.014355	89.83	1269.132	0	0	120	120	120.8
Oil 3	94	203	0.014355	89.83	1269.132	0	0	120	120	121
Oil 4	244	379	0.030266	64.125	4965.124	0	0	480	480	317.4
Oil 5	244	379	0.030266	64.125	4965.124	0	0	480	480	318.4
Oil 6	244	379	0.030266	64.125	4965.124	0	0	480	480	335.8
Oil 7	95	190	0.024027	76.129	2243.185	0	0	240	240	151
Oil 8	95	189	0.00158	81.805	2290.381	0	0	240	240	129.5
Oil 9	116	194	0.022095	81.14	1681.533	0	0	120	120	130
Oil 10	175	321	0.07681	46.665	6743.302	0	0	180	180	218.9
Oil 11	2	19	0.953443	78.412	394.398	0	0	90	90	5.4
Oil 12	4	59	0.000044	112.088	1243.165	0	0	90	90	45
Oil 13	15	83	0.072468	90.871	1454.74	0	0	300	300	20
Oil 14	9	53	0.000448	97.116	1011.051	0	0	162	162	16.3
Oil 15	12	37	0.059911	83.244	909.269	0	0	114	114	20

Please cite this article in press as: Bulbul SMA et al., Opposition-based krill herd algorithm applied to economic load dispatch problem, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.02.003

Table A1 (*continued*)

Unit	Pg^{min} (MW)	Pg^{max} (MW)	a (\$/MW^2 h)	b (\$/MW h)	c (\$/h)	d (\$/h)	e (rad/MW)	ur (MW)	dr (MW)	Po (MW)
Oil 16	10	34	0.244706	95.665	689.378	0	0	120	120	22.1
Oil 17	112	373	0.000042	91.202	1443.792	0	0	1080	1080	125
Oil 18	4	20	0.085145	104.501	535.553	600	0.070	60	60	10
Oil 19	5	38	0.524718	83.015	617.734	1200	0.043	66	66	13
Oil 20	5	19	0.176515	127.795	90.966	0	0	12	6	7.5
Oil 21	50	98	0.063414	77.929	974.447	0	0	300	300	53.2
Oil 22	5	10	2.740485	92.779	263.81	0	0	6	6	6.4
Oil 23	42	74	0.112438	80.95	1335.594	0	0	60	60	69.1
Oil 24	42	74	0.041529	89.073	1033.871	0	0	60	60	49.9
Oil 25	41	105	0.000911	161.288	1391.325	0	0	528	528	91
Oil 26	17	51	0.005245	161.829	4477.11	0	0	300	300	41
Oil 27	7	19	0.234787	84.972	57.794	0	0	18	30	13.7
Oil 28	7	19	0.234787	84.972	57.794	0	0	18	30	7.4
Oil 29	26	40	1.111878	16.087	1258.437	0	0	72	120	28.6

6. Test systems and simulation results

The proposed OKHA algorithm has been developed and implemented using the MATLAB software 7.10 on a personal computer (Pentium-IV processor, 500 GB, 4.0 GHz speed). The following input parameters of OKHA taken from [47] are adopted for this simulation study: the maximum induced speed, $V_i^{max} = 0.01$; the maximum diffusion speed $V_D^{max} = 0.05$; jumping probability $jr = 0.3$. The position constant factor, $P_t = 0.2$; the inertia weights, ω_n, ω_x are initially taken as 0.9 to emphasize exploration capability of the search process and these values are linearly decreased to 0.1 at the end to exploit the search space.

To verify the feasibility and efficiency of the proposed method we experimented with five standard test cases from the literature. In test system 2, simulation is carried out for different population size and corresponding results are presented in Table 1. It is observed from Table 1, that for population size less than 100, the proposed algorithm is unable to produce the optimal solutions and for population size more than 100, the computational time is increased without getting better solution. Therefore, the population size is taken as 100 throughout the simulation study. 50 individual trials are made and the best fuel cost and the corresponding generation value of each generator are presented in the corresponding Tables. With small description of the test systems are given below:

6.1. Description of test systems

6.1.1. Test system 1: Six unit system

In order to test the effectiveness of the proposed method, initially a small test system consisting of six generating units is considered. The detail system data are adopted from [49]. Load demand for this system is considered as 1263 MW [49]. The practical constraints of ELD problems such as prohibited operating zones and ramp-rate limits are considered to verify the efficacy of the proposed method under practical environment.

6.1.2. Test system 2: Ten unit system

A small test system consists of 10-thermal generating units with valve point effect and multi-fuel options are taken into consideration to test the competence of the algorithm. Total demand is taken as 2700 MW. For the sake of simplicity transmission line loss is not considered. The fuel cost coefficients of the thermal plant (a_i, b_i and c_i) and the data for multi fuel options are taken from [50].

6.1.3. Test system 3: Forty unit system

A medium typed system containing 40-generating units is used here to test the worthiness of proposed approach. For more realistic approach, valve point loading and transmission line losses are included without taking multi-fuel effect. The fuel cost coefficient of each generating unit is taken from [51] and the coefficient related to transmission line loss is adopted from [52]. The demand for this system is 10,500 MW.

6.1.4. Test system 4: One-forty unit system

To examine the superior quality of solution and robustness of the proposed OKHA method a relatively new large scale system is considered. This system, namely Korean power system consists of 140-thermal generating units. This test system is fossil fuel based power system, comprising of forty thermal generating units, fifty-one gas units, twenty nuclear unit and twenty-nine oil units. Out of 140-units, 6 thermal units, four gas units and two oil units have non-convex fuel cost function addressing valve loading effects. The input data are taken from [53] and also given in Table A1 in Appendix A. The other constraints like prohibited operating zones are not considered. The load demand is taken as 49,342 MW.

6.1.5. Test system 5: Wind-fossil fuel based 6-unit system

Finally, the effectiveness of the proposed OKHA and KHA methods is examined on a wind-fossil fuel based power system. This power system consists of two wind energy units, three thermal units, two gas units and an oil unit. The total load demand is taken as 1200 MW for this simulation study. The total system data are taken from [60].

6.2. Simulation results

6.2.1. Test system 1

The optimal generation scheduling of all six generators obtained by the proposed OKHA approach along with those obtained by other optimization techniques such as IPSO-TVAC [12], BFO [19], MTS [49], NPSO-LRS [54], GA [54], PSO [54], IPSO [55], NAPSO [56], SOH-PSO [57] and HHS [58] is listed in Table 2. It is observed from the simulation results that all system constraints such as the ramp rate limits and prohibited operating zones limits are satisfied. Furthermore, to judge the robustness of the proposed OKHA method, the statistical analysis for 50 independent runs is made. The worst, average and best fuel costs achieved by the different methods are shown in Table 3. It is observed that the worst, average and best cost obtained using OKHA are very close to each other representing the robustness of the proposed method. Cost convergence characteristic of OKHA algorithm is illustrated in Fig. 2.

6.2.2. Test system 2

The most economic fuel type, individual best generation and best value of fuel cost in 50 trials are tabulated in Table 4. The result is compared with recently published well settled optimization techniques such as PSO-LRS [59], NPSO [59], NPSO-LRS [59], APSO (2) [54], CBPSO-RVM [50] and KHA [47]. The total cost 605.6449 ($/h) given by OKHA is minimum compared to other algorithms without violation of the constraints mentioned in (4) and (7). This establishes the superiority and effectiveness of this proposed algorithm than other recently studied literature. The statistical comparison with other stated algorithms available in the literatures is summarized in Table 5 in 50 different independent trials. This reveals that best cost, mean cost and even worst cost are minimum by applying OKHA algorithm. This emphasizes the robustness of the proposed technique. The convergence characteristics of economical solution are demonstrated in Fig. 3. The convergence graph shows the computational efficiency of the algorithm.

6.2.3. Test system 3

Table 6 summarizes the test results in terms of optimum power generation dispatch for this system. The best solution to the fuel cost obtained by OKHA is 136,575.968 $/h which is better than those obtained by KHA-IV [47] (136,670.37 $/h), QOTLBO [21] (137,329.86 $/h), TLBO [21] (137,814.17 $/h), SDE [38] (138,157.46 $/h) and GA-API [52] (139,864.96 $/h). This clearly suggests that OGSA is better to get optimum solution of the ELD problems, in terms of quality of solution. Furthermore, to reveal the robustness of the proposed algorithm, its statistical results are compared with other evolutionary techniques. The statistical cost measurement tools such as best, mean and worst cost are represented in Table 7. It is clear from Table 7 that the statistical performance of OKHA algorithm is better than all other algorithms reported in the recent literature. Convergence characteristic of OKHA algorithm is plotted in Fig. 4.

6.2.4. Test system 4

The obtained results for the 140-unit system using the both KHA and OKHA are given in Table 8 and the results are compared with Shuffled differential evolution (SDE) [38]. It is observed that total fuel cost obtained by KHA gives 1,560,173.88 ($/h) which is less than SDE. And by applying OKHA, total generation cost is 1,560,146.95 $/h, which is the better solution compared to both SDE and KHA methods. Table 9 reveals a quantitative analysis of this test system for 50 different trials. The simulation results reported in Table 9 clearly show that the best cost, worst cost and the mean cost values obtained by the proposed method are comparatively less compared to all the other methods. So, it may be concluded that the algorithm used in this paper is feasible and indeed capable of acquiring better solution for large scale system. The convergence characteristics are given in Fig 5. From the presented results it can be found that best fuel cost obtained by OKHA is comparatively better than by other methods.

6.2.5. Test system 5

In order to judge the effectiveness of the OKHA and KHA methods for this wind based ELD problem, the proposed methods are tested on a wind-fossil fuel based 6-unit power system. To validate the superiority, the simulation results of OKHA and KHA are compared with those obtained by using previously published methods of QPSO [60] and GABC [61] methods. The optimum generation value of different generators, fuel cost (FC), wind cost (WC) and total cost (TC) obtained by OKHA and KHA along with QPSO and GABC are for load demand of 1200 MW is listed in Table 10. It is observed from the simulation results that generation cost obtained by OKHA (27,660.0238 $/h) is superior to that obtained by KHA (27,666.9493 $/h), QPSO (29,513.40 $/h) and GABC (27,710.00 $/h) without violating any operating constraint. A convergence characteristic of the proposed KHA algorithm is illustrated in Fig. 6.

7. Conclusion

The utilization of powerful optimization techniques in power systems with respect to various operational and planning practices has been one of the important and rapidly developing topics. ELD can be defined differently according to various viewpoints. One point of view considers the maximization of profit and minimization of production costs as priority. This paper presents a novel population based approach namely OKHA to solve ELD with nonconvex fuel cost functions as adopted by other heuristic approaches. The proposed algorithm is applied to ELD with valve point loading and ELD with multi-fuel effects and simulated to compare the test results with various population based approaches. The comparison shows the superiority of the proposed method and its potential for solving non-smooth ELD problems in a power system. By observing the solution quality, excellent convergence characteristics, computational efficiency of the algorithm, in future studies it can be applied in dynamic ELD problems, complex unit commitment problems and hydrothermal scheduling problem.

Appendix A

See Table A1.

References

[1] Victoire AAT, Jeyakumar AE. Hybrid PSO–SQP for economic dispatch with valve-point effect. Electr Power Syst Res 2004;71(1):51–9.

[2] Chatterjee A, Ghoshal SP, Mukherjee V. Solution of combined economic and emission dispatch problems of power systems by an

opposition-based harmony search algorithm. Int J Electr Power Energy Syst 2012;39(1):9–20.
[3] Wood AJ, Wollenberg BF. Power generation, operation and control. second ed. New York: Wiley; 1996. p. 29–88 [chapter 3].
[4] Jabr RA, Coonick AH, Cory BJ. A homogeneous linear programming algorithm for the security constrained economic dispatch problem. IEEE Trans Power Syst 2000;15(3):930–6.
[5] Chen C. Non-convex economic dispatch: a direct search approach. Energy Convers Manage 2007;48(1):219–25.
[6] Papageorgiou LG, Fraga ES. A mixed integer quadratic programming formulation for the economic dispatch of generators with prohibited operating zones. Int J Electr Power Energy Syst 2007;77(10):1292–6.
[7] Lee FN, Breipohl AM. Reserve constrained economic dispatch with prohibited operating zones. IEEE Trans Power Syst 1993;8:246–54.
[8] Ng K, Shelbe G. Direct load control–a profit-based load management using linear programming. IEEE Trans Power Syst 1998;13(2):688–94.
[9] Yang L, Fraga ES, Papageorgiou LG. Mathematical programming formulations for non-smooth and non-convex electricity dispatch problems. Electr Power Syst Res 2013;95:302–8.
[10] Liang ZX, Glover JD. A zoom feature for a dynamic programming solution to economic dispatch including transmission losses. IEEE Trans Power Syst 1992;7(2):544–50.
[11] Pereira-Neto A, Unsihuay C, Saavedra OR. Efficient evolutionary strategy optimization procedure to solve the nonconvex economic dispatch problem with generator constraints. IEE Proc Gener Trans Distrib 2005;152(5):653–60.
[12] Mohammadi-Ivatloo B, Rabiee A, Soroudi A, Ehsan M. Iteration PSO with time varying acceleration coefficients for solving non-convex economic dispatch problems. Int J Electr Power Energy Syst 2012;42(1):508–16.
[13] Da-kuo H, Fu-li W, Zhi-zhong M. Hybrid genetic algorithm for economic dispatch with valve-point effect. Electr Power Syst Res 2008;78(4):626–33.
[14] Panigrahi BK, Yadav SR, Agrawal S, Tiwari MK. A clonal algorithm to solve economic load dispatch. Electr Power Syst Res 2007;77(10):1381–9.
[15] Hou YH, Wu YW, Lu LJ, Xiong XY. Generalized ant colony optimization for economic dispatch of power systems. Int Conf Power System Tech, Power-Con 2002;1:225–9.
[16] Roy PK. Solution of unit commitment problem using gravitational search algorithm. Int J Electr Power Energy Syst 2013;53:85–94.
[17] Lin WM, Cheng FS, Tsay MT. An improved Tabu search for economic dispatch with multiple minima. IEEE Trans Power Syst 2002;17(1):108–12.
[18] Wong KP, Fung CC. Simulated annealing based economic dispatch algorithm. IEE Proc Gener Trans Distrib 1993;140 (6):509–15.
[19] Panigrahi BK, Pandi VR. Bacterial foraging optimisation: Nelder-Mead hybrid algorithm for economic load dispatch. IET Gener Trans Distrib 2008;2(4):556–65.
[20] Noman N, Iba H. Differential evolution for economic load dispatch problems. Electr Power Syst Res 2008;78(3): 1322–31.
[21] Roy PK, Bhui S. Multi-objective quasi-oppositional teaching learning based optimization for economic emission load dispatch problem. Int J Electr Power Energy Syst 2013;53:937–48.
[22] Rao RV, Savsani VJ, Vakharia DP. Teaching-learning-based optimization: a novel optimization method for continuous non-linear large scale problems. Inform Sci 2012;183(1):1–15.
[23] Roy PK. Teaching learning based optimization for short-term hydrothermal scheduling problem considering valve point effect and prohibited discharge constraint. Int J Electr Power Energy Syst 2013;53:10–9.
[24] Aydin D, Özyön S. Solution to non-convex economic dispatch problem with valve point effects by incremental artificial bee colony with local search. Appl Soft Comput 2013;13(5):2456–66.
[25] Basu M. Dynamic economic emission dispatch using nondominated sorting genetic algorithm-II. Int J Electr Power Energy Syst 2008;30(2):140–9.
[26] Coelho LDS, Mariani VC. Particle swarm approach based on quantum mechanics and harmonic oscillator potential well for economic load dispatch with valve-point effects. Energy Convers Manage 2008;49(11):3080–5.
[27] Cai J, Ma X, Li Q, Li L, Peng H. A multi-objective chaotic particle swarm optimization for environmental/economic dispatch. Energy Convers Manage 2009;50(5):1318–25.
[28] Roy PK, Ghoshal SP, Thakur SS. Combined economic and emission dispatch problems using biogeography-based optimization. Electr Eng 2010;92(4–5):173–84.
[29] Basu M. Artificial bee colony optimization for multi-area economic dispatch. Int J Electr Power Energy Syst 2013;49:181–7.
[30] Sahoo S, Dash KM, Prusty RC, Barisal AK. Comparative analysis of optimal load dispatch through evolutionary algorithms. Ain Shams Eng J 2015;6(1):107–20.
[31] Zhisheng Z. Quantum-behaved particle swarm optimization algorithm for economic load dispatch of power system. Expert Syst Appl 2010;37(2):1800–3.
[32] Zare K, Haque MT, Davoodi E. Solving non-convex economic dispatch problem with valve point effects using modified group search optimizer method. Electr Power Syst Res 2012;84(1):83–9.
[33] Roy PK, Mandal D. Oppositional biogeography-based optimization for optimal power flow. Int J Electr Power Energy Syst 2013;53:123–34.
[34] Roy PK, Mandal D. Quasi-oppositional biogeography-based optimization formulti-objective optimal power flow. Electr Power Compon Syst 2011;40(2):236–56.
[35] Bhattacharya A, Chattopadhyay PK. Hybrid differential evolution with biogeography-based optimization for solution of economic load dispatch. IEEE Trans Power Syst 2010;25 (4):1955–64.
[36] Jadhav HT, Roy R. Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power. Expert Syst. Appl. 2013;40(16):6385–99.
[37] Shanhe J, Zhicheng J, Yanxia S. A novel hybrid particle swarm optimization and gravitational search algorithm for solving economic emission load dispatch problems with various practical constraints. Int J Electr Power Energy Syst 2014;55:628–44.
[38] Reddy AS, Vaisakh K. Shuffled differential evolution for large scale economic dispatch. Electr Power Syst Res 2013;96:237–45.
[39] Dogan A, Serdar O. Solution to non-convex economic dispatch problem with valve point effects by incremental artificial bee colony with local search. Appl Soft Comput 2013;13:2456–66.
[40] Suresh CV, Sivanagaraju S. Analysis and effect of multi-fuel and practical constraints on economic load dispatch in the presence of Unified Power Flow Controller using UDTPSO. Ain Shams Eng J 2015;6(3):803–17.
[41] Kumar YNV, Sivanagaraju S, Suresh CV. Security constrained economic load dispatch in the presence of interline power flow controller using modified BAT algorithm. Ain Shams Eng J 2015 (in press).
[42] Roy PK, Bhui S, Paul C. Solution of economic load dispatch using hybrid chemical reaction optimization approach. Appl Soft Comp 2014;24:109–25.
[43] Chen C-L, Chen Z-Y, Lee T-Y. Multi-area economic generation and reserve dispatch considering large-scale integration of wind power. Int J Electr Power Energy Syst 2014;55:171–8.
[44] Ghasemi A. A fuzzified multi objective interactive honey bee mating optimization for environmental/economic power dispatch with valve point effect. Int J Electr Power Energy Syst 2013;49:308–21.

Please cite this article in press as: Bulbul SMA et al., Opposition-based krill herd algorithm applied to economic load dispatch problem, Ain Shams Eng J (2016), http://dx.doi.org/10.1016/j.asej.2016.02.003

[45] Roy PK, Bhui S. A multi-objective hybrid evolutionary algorithm for dynamic economic emission load dispatch. Int Trans Elect Energy Syst 2015 (in press).
[46] Gandomi AH, Alavi AH. Krill herd: a new bio-inspired optimization algorithm. Nonlin Sci Numer Simul 2012;17 (12):4831–45.
[47] Mandal B, Roy PK, Mandal S. Economic load dispatch using krill herd algorithm. Int J Electr Power Energy Syst 2014;57:1–10.
[48] Shaw B, Mukherjee V, Ghoshal SP. A novel opposition-based gravitational search algorithm for combined economic and emission dispatch problems of power systems. Int J Electr Power Energy Syst 2012;35(1):21–33.
[49] Pothiya S, Ngamroo I, Kongprawechnon W. Application of multiple tabu search algorithm to solve dynamic economic dispatch considering generator constraints. Energy Convers Manage 2008;49(4):506–16.
[50] Lu H, Sriyanyong P, Song YH, Dillon T. Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function. Int J Electr Power Energy Syst 2010;32 (9):921–35.
[51] Basu M. Economic environmental dispatch using multi-objective differential evolution. Appl Soft Comput 2011;11(2):2845–53.
[52] Ciornei I, Kyriakides E. A GA-API solution for the economic dispatch of generation in power system operation. IEEE Trans Power Syst 2012;27(1):233–42.
[53] Park JB, Jeong YW, Shin JR, Lee KY. An improved particle swarm optimization for nonconvex economic dispatch problems. IEEE Trans Power Syst 2010;25(1):156–66.
[54] Selvakumar AI, Thanushkodi K. A new particle swarm optimization solution to nonconvex economic dispatch problems. IEEE Trans Power Syst 2007;22(1):42–51.
[55] Safari A, Shayeghi H. Iteration particle swarm optimization procedure for economic load dispatch with generator constraints. Expert Syst. Appl. 2011;38(5):6043–8.
[56] Niknam T, Mojarrad HD, Meymand HZ. A new particle swarm optimization for non-convex economic dispatch. Euro Trans Electr Power 2011;21(1):656–79.
[57] Chaturvedi K, Pandit M, Srivastava L. Self-organizing hierarchical particle swarm optimization for non-convex economic dispatch. IEEE Trans Power Syst 2008;23(3):1079–87.
[58] Fesanghary M, Ardehali M. A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem. Energy 2009;34(6):757–66.
[59] Amjady N, Nasiri-Rad H. Solution of nonconvex and nonsmooth economic dispatch by a new adaptive real coded genetic algorithm. Expert Syst. Appl. 2010;37(7):5239–45.
[60] Yao F, Dong ZY, Meng K, Xu Z, Iu HH-C, Wong KP. Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia 2012. IEEE Trans Ind Inform 2012;8(4):880–8.
[61] Jadav HT, Roy R. Gbest guided artificial bee colony algorithm for environmental/economic dispatch considering wind power. Expert Syst Appl 2013;40:6385–99.

Sk Md Ali Bulbul was born in 15th November, 1986, at Burdwan, West Bengal, India. He received the BE degree in Electrical Engineering from Techno India College, Soltlake, Burdwan, India, in 2009; and ME degree from Dr. B.C. Roy Engineering College, Durgapur, India, in 2014. Presently, he is working as an Assistant Professor in the department of Electrical Engineering, Bengal College of Engineering and Technology, Durgapur, West Bengal, India. His field of research interest includes power systems operation, control and stability, economic load dispatch and evolutionary computing techniques.

Moumita Pradhan received her BTech degree in Computer Science and Engineering from JIS College of Engineering College, Kalyana (under West Bengal University of Technology), India, in 2005 and MTech degree from NIT, Durgapur, West Bengal, India, in Operation Research and Business management in 2009. Her area of research includes hydrothermal scheduling, economic load dispatch and soft computing techniques. Presently she is working as an Assistant Professor in the Department of Computer Science and Engineering, Dr. B.C. Roy Engineering College, Durgapur, India.

Dr. Provas Kumar Roy was born in 1973 at Mejia, Bankura, West Bengal, India. He received the BE degree in Electrical Engineering from R. E. College, Durgapur, Burdwan, India, in 1997; ME degree in Electrical Machine from Jadavpur University, Kolkata, India, in 2001 and PhD from NIT, Durgapur, in 2011. Presently he is working as an Associate Professor in the department of Electrical Engineering, Jalpaiguri Government Engineering College, Jalpaiguri, India. He has published more than 80 research papers in international journals and conferences. His field of research interest includes Economic Load Dispatch, Optimal Power flow, FACTS, Unit Commitment, Automatic Generation Control, Power System Stabilizer and Evolutionary computing techniques.

Dr. Tandra Pal received her B.Tech. degree in Computer Science and Engineering from Calcutta University, India, and M. E. Degree from Jadavpur University in Computer Science and Engineering. She received her PhD degree from Jadavpur University in Engineering. Her area of research includes Computational Intelligence (CI)/Soft Computing, Multi Objective Genetic Algorithms and their Applications, Fuzzy Logic, Artificial Neural Network, Pattern Recognition, Fuzzy Logic Controllers. She has published 39 research papers in national and international journals and conferences. She is an Associate Professor in the Department of Computer Science and Engineering, National Institute of Technology, Durgapur, India, E-mail: tandra.pal@gmail.com.